Enhancing and Scaling Cross-Modality Alignment for Multimodal Pre-Training via Gradient Harmonization

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Abstract

Self-supervised pre-training recently demonstrates success on large-scale multimodal data, and state-of-the-art contrastive methods often enforce the feature consistency from cross-modality inputs, such as video/audio or video/text pairs. Despite its convenience to formulate and leverage in practice, such cross-modality alignment (CMA) is only a weak and noisy supervision, since two modalities can be semantically misaligned even they are temporally aligned. For example, even in the (often adopted) instructional videos, a speaker can sometimes refer to something that is not visually present in the current frame; and the semantic misalignment would only be more unpredictable for the raw videos collected from unconstrained internet sources. We conjecture that might cause conflicts and biases among modalities, and may hence prohibit CMA from scaling up to training with larger and more heterogeneous data. This paper first verifies our conjecture by observing that, even in the latest VATT pre-training using only narrated videos, there exist strong gradient conflicts between different CMA losses within the same sample triplet (video, audio, text), indicating them as the noisy source of supervision. We then propose to harmonize such gradients during pre-training, via two techniques: (i) cross-modality gradient realignment: modifying different CMA loss gradients for one sample triplet, so that their gradient directions are in more agreement; and (ii) gradient-based curriculum learning: leveraging the gradient conflict information on an indicator of sample noisiness, to develop a curriculum learning strategy to prioritize training with less noisy sample triplets. Applying those gradient harmonization techniques to pre-training VATT on the HowTo100M dataset, we consistently improve its performance on different downstream tasks. Moreover, we are able to scale VATT pre-training to more complicated non-narrative Youtube8M dataset to further improve the state-of-the-arts. We will open-source our codes and models.

1 Introduction

Self-supervised pre-training scales up deep learning to leverage massive unlabeled data. Beyond the maturity of pre-training over single-modality data such as language [2] or images [3], the recent success on multimodal pre-training [4, 5] demonstrates the versatility to synergize the rich multimodal information and to benefit a variety of downstream tasks. Many methods of this category [6, 7, 8, 4], especially the latest contrastive pre-training methods [5, 9, 10, 11], consider the most organic supervision as the *cross-modality alignment* (**CMA**), e.g., in the same video sequence, the video frames, audio stream, and text scripts are temporally aligned and hence should naturally have correspondence. Such assumed cross-modal correspondence could be exploited as "mutual supervision" for each modality to learn consistent semantic features with each other. For example,

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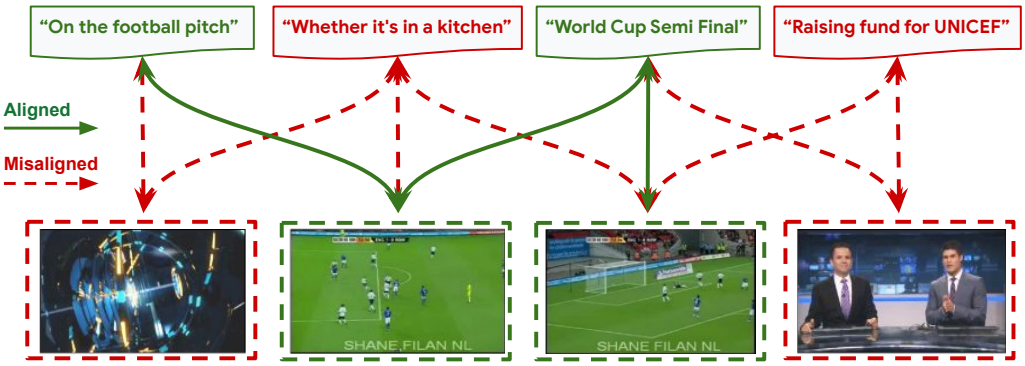


Figure 1: Examples of cross-modality alignment and misalignment existing in the complicated and non-narrative Youtube8M dataset [1]. Here we show a video sequence whose themes is a football match, where (a) the text mentions content unrelated to the football, e.g., "kitchen","raising fund"; and (b) the visual content is also unrelated to the football, e.g., TV cutscenes, the scene of the broadcast studio, etc.

the latest Video-Audio-Text Transformer (VATT) [11] hinges on this multimodal CMA *a priori* to train a transformer-based architecture (even a single backbone by sharing weights among the three modalities), using two contrastive losses to align video-text and video-audio pairs, respectively. Their results set many new records in downstream tasks with neither supervised pre-training nor predefined inductive biases, showing strong "universal" generalizability despite the modality and the domain gaps.

Unfortunately, the CMA assumption rests on a very shaky foundation, especially for uncurated videos collected in the wild. The CMA can be weak even for the instructional videos such as HowTo100M [12] that are commonly adopted as the current multimodal pre-training data source. For instance, a speaker can refer to something before or after actually demonstrating it visually; she or he could also skip verbally explaining something that is visually happening, because that may be trivial or be already clear enough in the visual context [13]. Such discrepancy would be amplified if considering many other outliers in video (e.g. background objects) or language (e.g. off-topic small talks). The semantic misalignment will be even more severe, and in unpredictable forms, when we go beyond instructional videos and explore training with non-narrative, free-from internet videos. Figure **??** shows a few examples of such cross-modal misalignment in the non-narrative Youtube8M dataset [1], which would put CMA-guided pre-training in jeopardy. This important problem is yet under-studied in the self-supervised multimodal pre-training literature. That said, there has been a few recent efforts such as Multiple-Instance Learning (MIL) NCE [13] and noisy pair pruning as in [14].

We conjecture that the vanilla CMA might provide only weak, noisy and even misleading supervision for multimodal pre-training; hence it might constitute a hidden bottleneck when scaled up with more realistic data (beyond instructional videos) whose modalities are poorly aligned. We verify this conjecture by inspecting two large-scale multimodal datasets, HowTo100M [15] and Youtube8M [1]. Specifically, when we adopt pairwise CMA losses (e.g. video-audio, video-text) within the cross-modal sample triplets (video, audio, text), a majority of the gradients strongly conflict with each other in terms of their directions, indicating the noisy and misaligned supervision. The cross-modal conflict not only causes unstable training convergence, it also causes modality-specific overfitting; e.g. semantically strong representations for one modality and meaningless representations for another modality.

Having identified this gap, we propose to harmonize those gradients so that they become mutually compatible in learning the unified representations. Specifically, we introduce two techniques: (i) cross-modal gradient realignment, where we modify different pairwise CMA loss gradients to align their directions for the same sample triplet, using gradient surgery [16] developed for multi-task learning; and (ii) gradient-based curriculum learning, where we leverage the gradient conflict information to indicate sample noisiness (e.g. a triplet whose CMA gradients are in more agreement is considered less "noisy" and would be prioritized for cross-modal pre-training) and a curriculum learning strategy is developed accordingly. Both techniques are found to boost VATT performance on downstream tasks, not only on instructional videos, but even more when the more complicated non-narrative data is involved.

Our contributions can be summarized as the following:

- We suggest that the commonly assumed CMA might be an important yet overlooked performance hurdle for scaling up multimodal pre-training, and we observe severe misalignment even from the state-of-the-art (SOTA) model [11] on the relatively aligned data [12].
- We propose to consistently improve the pre-training pipeline in the only baseline in this direction, VATT (modality-agnostic setting), resulting in better downstream performance.
- With the help of our proposed techniques, we consistently improve the pre-training of VATT, resulting in better downstream performance, e.g. up to 58% gain in the rank metric of video-text retrieval task. Moreover, we are able to scale VATT pre-training to more complicated non-narrative Youtube8M dataset, which further yields new state-of-the-art performance in a modality-agnostic setting.

2 Related Work

2.1 Self-Supervised Multimodal Pre-training

The most organic self-supervision can arguably be found in the multimodal data that are abundantly available in the digital world: their temporal alignment naturally lead to cross-modality mutual supervision, hence meaningful features can be learned without requiring human annotation. Multimodal pre-training can thus leverage richer semantic cues than single-modality counterparts, and outperform in various downstream tasks such as image classification [5, 11], video action recognition [5, 11, 13, 10], audio event classification [5, 11, 10], and video-text retrieval [5, 11, 13]. Most of those methods formulate pre-text tasks, including cross-modality correspondence [6, 7, 8, 10], cross-modality clustering [17], cross-modality longer context prediction [18], or a combination of multiple pre-text tasks [19].

Contrastive learning [3, 20] has recently emerged as the dominant approach in self-supervised learning. In multimodal pre-training, the temporal co-occurrence naturally supplies the positive sample to contrast with. [5] adopts a multimodal versatile network to embed each modality into the same vector space, that is trained from end to end with multimodal pairwise contrastive losses (video-audio, and video text). CrossCLR [9] further takes the intra-modality similarities into account. [10] generalizes the instance discrimination idea to design a cross-modal discrimination task, i.e., predicting which audio matches a video. Most recently, VATT [11] combines the strength of convolution-free Transformer and multimodal contrastive learning. Specifically, it first validate the idea of using a modality-agnostic single-backbone transformer, to work on video, audio and text modalities, it follows the exact BERT [21] and ViT [22] architecture, except injecting modality-specific tokenization layers and linear projections.

Despite their success, existing multimodal contrastive learning methods [5, 9, 11] hinge on the "free" cross-modalities correspondence mined through the multimodal contrastive loss, i.e., the CMA assumption. As a result, they are often trained with relatively well curated or narrated video datasets, such as AudioSet [23], YouCook2 [15], and HowTo100M [12]. It remains questionable whether such CMA-guided contrastive learning can generalize well to larger-scale multimodal data in the wild. In fact, even in the HowTo100M dataset, the authors of [12] estimate that around 50% of clip-narration pairs are not well aligned.

The validity of CMA recently arises some attention. Most related to us is [13] which explicitly models the misalignment noise using the MIL-NCE loss, that is inherited by VATT [11].

2.2 Multi-task versus Multimodal Learning

While earlier self-supervised works used different modality-specific encoders, the latest multimodal pre-training sees a tendency to explore a versatile and "universal" model shared across modalities [5, 11]. It is easy to notice the resemblance between multimodal learning (especially with a unified backbone) and multi-task learning [24, 25]. The later often assumes multiple tasks to share transferable knowledge and can help each other learn. Yet in practice, different tasks can be heterogeneous in nature too, often leading to heavily misaligned gradient scales [26] or directions [16]. Such conflicting gradients from multiple losses would lead to several undesirable effects, including (i) strong bias towards learning some tasks with largest gradient scales; and (2) slow and unstable convergence. Similar problems are often faced by multimodal pre-training too.

As a result, several works have been developed to mitigate the gradient dilemma in multi-task learning. Methods such as gradient normalization [26] and adaptive loss weight [27, 28] address the gradient

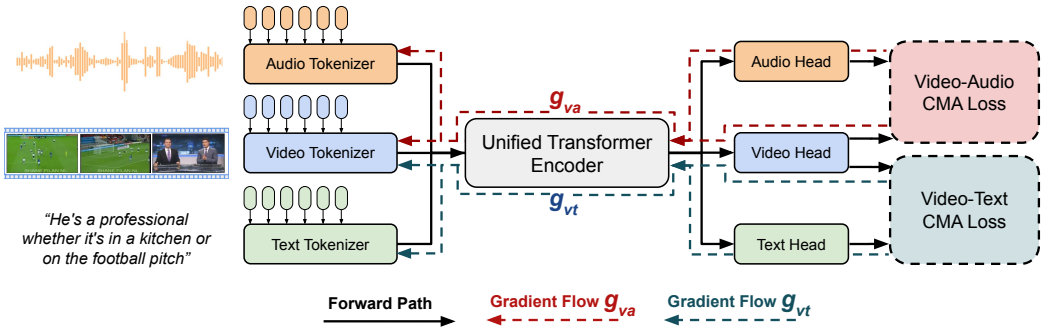


Figure 2: One main model used in this paper: the VATT model [11] with a modality-agnostic, single-backbone Transformer by sharing weights among the three modalities. VATT is trained with two contrastive losses between video-audio and video-text pairs, respectively. The positive cross-modality pairs to contrastive with are based on their temporal co-occurrence (e.g., the CMA assumption). We primarily study the conflicts between gradients g_{va} and g_{vt}, which indicate the often poor alignments, and discuss how to harmonize their conflicts.

scale/learning speed imbalance issues. Gradient surgery [16] tries to project gradients with conflicting directions onto the normal plane of each other, to prevent each gradient's interfering component from being applied to the network. Later, Gradient vaccine [29] further generalizes this idea extending the gradient projection to arbitrary angle, and uses the exponential moving average of cosine similarity to measure the alignment between different tasks. When it comes to the multimodal learning, [30] investigates optimally blending modality-specific gradients by linearly re-scaling them. Meanwhile, to our best knowledge, there has been no prior study on modality-specific gradient directions.

3 Methodology

Pre-requisites: Without loss of generality, we focus on the SOTA multimodal contrastive learning model, VATT [11], as our default subject of study; and we follow its modality-agnostic single-backbone setting due to its compelling performance-efficiency trade-off, and due to the fact that it is the most intuitive setting to modify gradients (shared between paired modalities) w.r.t different end-point objectives.

In our modality-agnostic single-backbone setting of VATT, the goal of pre-training is to find the parameter θ of the model f_θ to learn meaningful features for all target modalities (video, audio, text), usually measured by a set of pairwise similarity metrics. VATT uses two pairwise contrastive losses for video-audio and video-text respectively to solve cross-modal alignment:

$$\min_{\theta} \ \text{CMA}_{va}(\theta) + \text{CMA}_{vt}(\theta) \tag{1}$$

where CMA_{va} and CMA_{vt} penalize the cross-modal alignment for video-audio and video-text pairs, using the Noise-Contrastive Estimation objective [31], respectively.

Figure 2 illustrates the VATT pipeline. First, video-audio-text triplets are sampled from random temporal locations, and then video-text and video-audio pairs are formed accordingly. Positive pairs are formed by selecting the two modalities at the same temporal locations from the same video clip; while the negative pairs are obtained by randomly sampling any video, audio, or text from other video clips. We follow the convention in [5, 11] to use the vanilla NCE loss for video-audio pairs, and to use the MIL-NCE loss proposed in [13] to align video-text pairs. Hence, CMA_{va} and CMA_{vt} are defined as follows:

$$\text{CMA}_{va}(\theta) = -\log\left(\frac{\exp(z_v^\top z_a/\tau)}{\exp(z_v^\top z_a/\tau) + \sum_{z'\in\mathcal{N}} \exp({z'}_v^\top {z'}_a/\tau)}\right) \tag{2}$$

$$\text{CMA}_{vt}(\theta) = -\log\left(\frac{\sum_{z_t\in\mathcal{P}_k(z_t)} \exp(z_v^\top z_t/\tau)}{\sum_{z_t\in\mathcal{P}_k(z_t)} \exp(z_v^\top z_t/\tau) + \sum_{z'\in\mathcal{N}} \exp({z'}_v^\top {z'}_t/\tau)}\right) \tag{3}$$

where $\mathcal{N}$ is the pool of negative pairs, $\mathcal{P}_k(z_t)$ denotes the k-neighbouring narrations surrounding the original text z_t. The gradients of two pairwise losses CMA_{va} and CMA_{vt}, denoted as g_{va} and g_{vt}, will be together applied (i.e. simple adding) to updating the model f_θ.

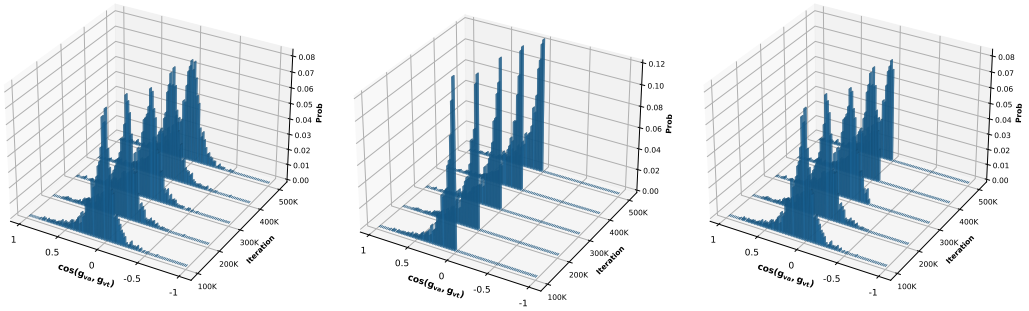
3.1 Observation of Conflicting Gradients

While qualitatively recognizing the cross-modal misalignment is easy, it is a highly challenging endeavor to quantify the misalignment and to automatically find misaligned triplets at scale, due to the vaguely defined criterion as well as the absence of labels [13, 14]. Therefore, the foremost need is to identify a *surrogate indicator* on how noisy the alignment of a sample triplet is, without making unrealistic assumptions nor incurring much computational overhead.

Our empirical choice of surrogate indicator is the directional alignability (i.e., vector angle) of gradients generated by different pairwise cross-modal losses, i.e., the **cosine similarity** between g_{va} and g_{vt} in the particular example of VATT, after flattening them into two vectors. The choice is firstly rationalized by the *coherent gradient hypothesis* [32], that healthy model training should witness the overall gradient stronger in certain directions along which the samples' gradients reinforce each other. Secondly, comparing the gradient directions between multiple pairwise losses could be considered as an ensemble or "cross-check": intuitively, if both video-audio and video-text pairwise consistency lead to the same update direction, then there is a good chance that those modalities are well aligned and the update direction is reliable; otherwise, at least one pair (video-audio, or video-text) might suffer from misalignment and CMA provides noisy guidance.

Overall, we conjecture that: *aligned video-text-audio triplets should have higher cosine similarity for g_{va} and g_{vt}, and vice versa*. We compute the cosine similarity between g_{va} and g_{vt} using the same setting as [32]. In the supplementary, We perform a sanity check for our conjecture by examining it qualitatively.

Using this surrogate indicator, we examine the cosine similarity between gradient g_{va} and g_{vt} (over 500k iterations) of VATT on the HowTo100M dataset [12]. In Figure 3a, we plot the distribution of cosine similarities, $cos(g_{va}, g_{va})$, across 500k iterations of pre-training. We observe that $cos(g_{va}, g_{va})$ at any iteration resembles a normal distribution, and about half of the gradients g_{va} and g_{va} have misaligned directions (negative cosine similarities). The plot echos the empirical finding in [15] that around 50% of video-text pairs are not well-aligned on the HowTo100M dataset. In the supplementary, we have included similar plots for the YouTube8M dataset [1]. Comparing those plots verify that non-narrative video sets have more severe misalignment than the narrative ones, hence challenging the CMA assumption even more.



(a) Multimodal pre-training baseline

(b) w/ Cross-Modality Gradient Realignment

(c) w/ Gradient-based Curriculum Learning

Figure 3: Visualization of cosine similarity between gradient g_{va} and g_{vt} across 500K Iterations on the HowTo100M dataset. (a) shows the baseline setting in multimodal pre-training; (b) with only cross-modality gradient realignment; (c) with only gradient-based curriculum learning. Youtube8M follows very similar observations, see supplementary.

The existence of conflicting gradients not only makes the convergence harder, but also makes the learned representation heavily overfit some modalities. In our case, we observe the training to be biased towards video/audio modalities, which favors the downstream performance of video/audio classification task, yet sets back the performance of video-to-text retrieval task (verified in Table 1).

3.2 Harmonizing Gradients during Pre-training

We present two strategies to mitigate the conflicting gradients: a "hard" way to project gradient directions, and a "soft" way to progressively select sample triplets in curriculum.

3.2.1 Cross-Modality Gradient Realignment

Since g_{va} and g_{vt} are misaligned in terms of their directions, one natural idea is to re-align the cross-modality gradients, by enforcing or re-projecting their directions to be aligned. An intuitive choice is an effective remedy developed for multi-task learning named Gradient Surgery [16]. Here, instead of applying it to g_i and g_j where i, j are the two heterogeneous tasks, we apply it to g_{va} and g_{vt}, which refer to the gradients of the two pairwise losses CMA_{va} and CMA_{vt} w.r.t the weights in the model, following our rationale in Section 3.1. If the gradients g_{va} and g_{vt} have negative cosine similarity, we alter them by projecting each onto the normal plane of the other. Otherwise, if g_{va} and g_{vt} have zero or positive similarity, we retain the original gradients. We refer to this particularly adapted form of gradient surgery as *Cross-Modality Gradient Realignment*. Its update procedure is outlined in Algorithm 1, and the overhead very cheap, mainly just computing inner products of two flattened gradients.

Algorithm 1 Cross-Modality Gradient Realignment

Require: Model parameter θ , minibatches $\mathcal{B}_{va}$, minibatches $\mathcal{B}_{vt}$
for $(b_{va}, b_{vt}) \in (\mathcal{B}_{va}, \mathcal{B}_{vt})$ **do**
  $g_{va} \leftarrow \nabla_\theta \text{CMA}_{va}(\theta)$, $g_{vt} \leftarrow \nabla_\theta \text{CMA}_{vt}(\theta)$
  $g_{va} \leftarrow \text{flatten}(g_{va})$, $g_{vt} \leftarrow \text{flatten}(g_{vt})$
  $\hat{g}_{va} \leftarrow g_{va}$, $\hat{g}_{vt} \leftarrow g_{vt}$
  if $g_{va} \cdot g_{vt} < 0$ **then**
    $\hat{g}_{va} \leftarrow \hat{g}_{va} - \frac{\hat{g}_{va} \cdot g_{vt}}{||g_{vt}||^2}$ ▷ projection $g_{vt} \leftarrow g_{va}$
    $\hat{g}_{vt} \leftarrow \hat{g}_{vt} - \frac{\hat{g}_{vt} \cdot g_{va}}{||g_{va}||^2}$ ▷ projection $g_{va} \leftarrow g_{vt}$
  end if
  $\hat{g}_{va} \leftarrow \text{reshape}(\hat{g}_{va})$, $\hat{g}_{vt} \leftarrow \text{reshape}(\hat{g}_{vt})$
  $\Delta\theta \leftarrow \hat{g}_{vt} + \hat{g}_{va}$ ▷ sum up gradients
  update θ with $\Delta\theta$ ▷ update parameter
end for

Additionally, we also tried another similar algorithm named Gradient Vaccine [29], and the results are almost fully consistent and comparable to using Gradient Surgery [16]. We hence only report one for the sake of conciseness.

3.2.2 Gradient-based Curriculum Learning

We next propose a gradient-based curriculum learning strategy that gradually identifies and removes more misaligned samples based on the similarity indicator as the training goes on. Formally, given a video-audio pair b_{va} and video-text pair b_{vt}, we only update the parameter if $cos(g_{va}, g_{va}) > \gamma$ and drop this sample triplet otherwise. This ensures us to gradually prioritize training with well-aligned samples while suppressing the noisy supervision from potentially misaligned samples. The drop rate here is controlled by a hyperparameter γ. In general, γ is a negative value monotonically increasing during training, and there is an underlying rationale. Initially, the network is under-trained and the similarity between its learned features is not reliable to indicate a strong CMA; hence we are more conservative in excluding samples. As the network becomes more sufficiently trained, the features become more semantically aligned, allowing us to remove more misaligned samples in the later stage of training. The full procedure of Gradient-based Curriculum Learning is outlined in Algorithm 2. We empirically choice $\gamma_0 = -0.3$ at the beginning and linearly increase it to $\gamma_{500K} = 0$ at the end, we include an ablation on the adaptive choice of γ in the Table 2.

Algorithm 2 Gradient-based Curriculum Learning

Require: Model parameter θ, minibatches $\mathcal{B}_{va}$, minibatches $\mathcal{B}_{vt}$, initial γ_0
for $(b_{va}, b_{vt}) \in (\mathcal{B}_{va}, \mathcal{B}_{vt})$ **do**
  update γ ▷ curriculumly update γ
  $g_{va} \leftarrow \nabla_\theta \text{CMA}_{va}(\theta)$, $g_{vt} \leftarrow \nabla_\theta \text{CMA}_{vt}(\theta)$
  $g_{va} \leftarrow \text{flatten}(g_{va})$, $g_{vt} \leftarrow \text{flatten}(g_{vt})$
  if $g_{va} \cdot g_{vt} > \gamma$ **then**
    $g_{va} \leftarrow \text{reshape}(g_{va})$, $g_{vt} \leftarrow \text{reshape}(g_{vt})$
    $\Delta\theta \leftarrow g_{va} + g_{vt}$ ▷ sum up gradients
    update θ with $\Delta\theta$ ▷ update parameter
  end if
end for

Similar classes of ideas, i.e, “gradually focusing a small training subset", have been explored by a prominent class of algorithms which rely on sample selection to robustify [33, 34, 35] or to accelerate [36] training. Most of them use the “small loss trick" wherein a fraction of samples with smallest loss values below a certain threshold are considered as reliable. However, they did not explore gradient conflict indicators, which targets solving our CMA problem here. Also note that our two steps can fully reuse the cosine similarity computed, so applying them together incurs no extra overhead.

4 Experiments

4.1 Pre-Training Datasets and Settings

In this paper, we focus on studying gradients in a modality-agnostic single-backbone setting, thus we do not consider multimodal pre-training baseline with modality-specific models, e.g. HERO[37], MMV[5], PerceiverIO[38], AVLnet[39]. Apart from VATT[11], there exist other concurrent work that use modality-agnostic setting[19, 40, 41], yet they all have their respective limitations. For example, UniVL[19] lacks audio modalities thus cannot constitute video-audio CMA loss, VLM[40] applies separate attention mask for each modality while PolyViT[41] use alternate training between modalities and tasks, thus eliminate the possibilities of any gradients conflicts. Therefore, this leave VATT[11] to be the most suitable baseline besides it SoTA performance.

Our pre-training adopts three settings for comprehensive comparison: **(1)** using HowTo100M as our training set, following [19, 12]; **(2)** combining HowTo100M and AudioSet as our training set following [5] and VATT [11]; and **(3)** additionally merging a noisy Youtube8M dataset alongside with HowTo100M and AudioSet, to create a much more compound and complicated training set than considered before, to stretch-test our proposal's benefits to scale up pre-training in uncurated and poorly aligned data. For each setting, we i.i.d sample video-audio-text clips from the mixture of all candidate sets in every batch. (HowTo100M, Audioset or Youtube8M, if applicable). For all setting, we only use a subset of HowTo100M, AudioSet, Youtube8M, Kinetics400 and Youcook2 dataset in compliance with Youtube's wipe-out policies.

HowTo100M[1]**[12]** is a large-scale dataset of narrated videos with an emphasis on instructional videos that have well synchronized modalities. The training set consists of 127 Millions video clips with the corresponding close-captioned text from automatic speech recognition (ASR).

AudioSet[1]**[23]** is a large-scale audio-visual dataset originally intended for audio event classification. It consists of 1.78 Million 10-second clips sampled from Youtube Videos that contains a variety of audio tracks, such as musical instruments, animals or mechanical sounds.

Youtube8M[1]**[1]** is a large-scale video classification dataset based on Youtube videos. It consists of a diverse vocabulary of 3862 visual entities and a total number of 8 Million videos. To the best of our knowledge, we are the first to scale contrastive multimodal pre-training beyond instructional videos, onto this noisy Youtube8M videos that more faithfully represent videos the wild. For data pre-processing, we split each video into 5s clips and use ASR close-captions to generate the corresponding text, resulting in 165 Millions video-audio-text clips.

4.2 Pre-Training Settings

Network Architecture: For all of our experiments, we use modality-agnostic Transformer variant in [11], VATT-MA-Medium. Specifically, we use a 12-layer Transformer, in which each Transformer module has a feed-forward MLP with hidden size of 4096, and 16 attention heads with a hidden size of 1024.

Pre-training Hyperparameter: We strictly follow the setting in [11], pre-training VATT from scratch with Adam optimizer with an initial learning rate of 1e-4, 10k warmup steps, 500k steps in total, a batch size of 2048 and using a cosine learning rate scheduler to anneal the learning rate from 1e-4 to 5e-5. Our framework is implemented in Tensorflow 2.8, and train with 256 TPUV3s, it took a total of 3 days to train our models.

4.3 Downstream Tasks for Evaluation

We evaluate the performance of our pre-trained representations when tuned towards various downstream tasks, including a variety of video/audio and cross modalities tasks.

Video Action Recognition: Following [5], we evaluate on UCF101[42] (101 action classes, 13,320 videos) and the HMDB51[43] (51 classes, 6,766 videos) benchmarks. For both settings, we directly attach a linear classifier on the learned representations while freezing the transformer backbone. We also evaluate on Kinetics400[1][44] dataset (400 classes, 234,584 video), where we fine-tune the transformer backbone.

Audio Event Classification: Following [5], we used ESC50[45] (50 classes, 2000 audio clips) as the benchmark for audio modalities. Similarly, we directly attach and tune a linear classifier on top of the frozen transformer backbone.

Zero-shot Video-Text Retrieval: To evaluate our performance on cross-modality task, we follow [5] using YouCook2[1][15] (3.1K video-text clips) and MSR-VTT[1][46] (1K video-text clips) as our evaluation datasets. We directly use the embedding from the pre-trained model without any fine-tuning, and report the recall at 10 (R@10) and Median Rank as described in [5].

Dataset	Tasks	Video Action Cls						Text-Video Retrieval				Audio Cls	
	Dataset	UCF101		HMDB51		Kinetics400		YouCook2		MSRVTT		ESC50	
	Metric	Top1↑	Top5↑	Top1↑	Top5	Top1↑	Top5↑	Rank↓	R@10↑	Rank↓	R@10↑	Top1↑	Top5↑
HT100M	VATT [11]	78.53	95.24	57.36	86.07	74.71	92.69	93.50	17.10	73.00	16.70	71.50	91.75
	+ RW (VA)	78.24	95.01	**58.74**	85.39	70.55	90.41	168.90	9.24	100.20	13.56	71.56	93.02
	+ RW (VT)	78.03	95.35	58.23	**86.80**	75.66	92.80	90.35	19.26	62.50	18.02	71.29	91.38
	+ GR	78.44	95.37	54.38	83.64	**76.72**	92.72	47.00	24.94	68.00	19.20	69.00	93.00
	+ CL	**79.10**	**96.16**	56.41	86.06	**77.25**	**93.38**	**40.00**	**26.01**	**56.00**	**23.90**	**72.50**	**94.25**
	+ Both	**79.24**	**96.58**	**58.24**	**87.37**	76.59	**93.26**	**42.00**	**25.87**	**54.00**	**24.50**	**72.05**	**94.16**
HT100M + AudioSet	VATT [11]	84.40	-	63.10	-	79.23	94.30	34.00	29.00	**67.00**	**23.60**	81.20	-
	+ RW (VA)	83.44	97.28	59.55	88.02	76.56	93.52	238.50	6.80	147.00	12.30	81.75	97.25
	+ RW (VT)	84.42	97.49	62.30	86.61	78.59	94.17	76.00	18.72	120.00	15.20	80.75	96.75
	+ GR	84.77	97.38	62.30	**90.38**	**79.29**	94.32	**29.00**	**31.65**	70.00	**21.40**	81.50	**97.00**
	+ CL	**86.04**	**97.75**	**65.45**	88.94	**79.89**	**94.71**	33.00	29.17	**65.50**	20.97	**82.00**	**97.25**
	+ Both	**85.46**	**97.58**	**65.52**	**89.74**	79.26	**94.48**	**31.50**	**30.26**	69.50	19.96	**82.00**	**97.00**
HT100M + AudioSet + YT8M	VATT [11]	88.28	**98.73**	**65.84**	91.43	79.39	94.56	**29.00**	29.66	56.00	26.90	80.75	97.00
	+ RW (VA)	86.97	98.09	61.06	89.66	77.70	93.83	99.00	14.25	75.50	19.70	83.50	97.25
	+ RW (VT)	88.19	97.96	61.13	90.51	78.43	94.38	**27.00**	31.07	48.50	27.70	82.25	96.75
	+ GR	87.49	98.10	60.99	88.35	**79.73**	94.57	32.00	29.56	60.00	27.20	**85.00**	**98.00**
	+ CL	**89.02**	98.33	**65.77**	**92.15**	79.70	**94.80**	31.00	**31.34**	**48.50**	**28.70**	83.50	**97.75**
	+ Both	**89.70**	**98.35**	64.35	**92.08**	**80.01**	**94.69**	**29.00**	**31.86**	**45.00**	**29.10**	**84.50**	**98.00**

Table 1: Results of pre-training on HowTo100M, AudioSet and Youtube8M dataset. *best* results are highlighted in **blue**, *second best* results are highlighted in **light blue**. RW(VA): Gradient Re-weighting (Scale up Video-Audio), RW(VT): Gradient Re-weighting (Scale up Video-Text), GR: Cross-Modality Gradient Realignment, CL: Gradient-based Curriculum Learning. (best view in color)

4.4 Result Analysis on HowTo100M and AudioSet Pre-training

Gradient Re-weighting We set up a simple gradient re-weighting baseline similar to [30], where we simply scale up the gradient magnitude of g_{va} by 2.5 times and scale down the gradient magnitude of its counterpart g_{vt} by 0.5 times, we denote this baseline as Gradient Re-weighting (VA), we also did it vice versa and denoted it as Gradient Re-weighting (VT). As shown in Table 1, we did not observe much performance boost with gradient re-weighting, on the contrary, there are significant performance drop in Text-Video Retrieval task on both YouCook2 and MSRVTT datasets.

Cross-Modality Gradient Realignment Compared to Gradient Re-weighting, our Cross-Modality Gradient Realignment mitigates the gradient conflicts by modifying gradients direction. In Table 1, we can see significant performance gains in video-text retrieval task (e.g. 58% gain in rank metric on YouCook2, 46% gain in R@10 metric on MSR-VTT), while maintaining a comparable performance in video/audio tasks. Since video-text retrieval task heavily hinge on cross-modality alignment (CMA), this improvement verify the benefits of re-aligning the cross-modality gradients.

Gradient-based Curriculum Learning Compared to Cross-Modality Gradient Realignment, Gradient-based Curriculum Learning inherents its performance gains in video-text retrieval task, yet enjoy an additional performance boost in audio classification (e.g. 1.40% gain ESC50 dataset in Table 1) and video classification (e.g. 1.94% gains UCF101 dataset in Table 1). We also perform an ablation on the adaptive choice of γ on Howto100M dataset in Table 2. We can see that curriculumly evolving γ (i.e.$(\gamma_0, \gamma_{500K}) = (-0.3, 0.0)$) yields the best overall results, while maintaining a fixed γ (i.e. $(\gamma_0, \gamma_{500K}) = (0.0, 0.0)$) yields the worst results, this verify the effectiveness of curriculumly removing mis-aligned samples during training.

Cross-Modality Gradient Realignment + Gradient-based Curriculum Learning We further verify the effectiveness with the combination of both techniques. Specifically, given a video-audio pair

[1]It is important to note that Howto100M, Youtube8M, AudioSet, Kinetics400, MSRVTT and YouCook2 videos are sourced from YouTube. Many of the videos have been made explicitly unavailable [47], hence we only train and evaluate over the subset of data that is publicly available at the time.

and video-text pair, (a) if $cos(g_{va}, g_{va}) \leq \gamma$, we drop this sample triplet; (b) if $\gamma < cos(g_{va}, g_{va}) < 0$, we apply gradient projection in Algorithm 1; (c) if $cos(g_{va}, g_{va}) \geq 0$, we retain the original gradients. We found they are complimentary to each other and the combination of both lead to better performance in the majority of downstream tasks.

	Hyperparameter	Video Action Cls				Text-Video Retrieval				Audio Cls	
	Dataset	UCF101		HMDB51		YouCook2		MSRVTT		ESC50	
	Metric	Top1↑	Top5↑	Top1↑	Top5	Rank↓	R@10↑	Rank↓	R@10↑	Top1↑	Top5↑
VATT [11]		78.53	95.24	**57.36**	86.07	93.50	17.10	73.00	16.70	71.50	91.75
+ CL	$(\gamma_0, \gamma_{500K}) = (-0.3, 0.0)$	**79.10**	**96.16**	56.41	86.06	**40.00**	**26.01**	**56.00**	**23.90**	**72.50**	94.25
	$(\gamma_0, \gamma_{500K}) = (-0.2, 0.0)$	77.75	94.94	56.87	**87.18**	53.00	22.21	57.00	20.80	70.75	**94.75**
	$(\gamma_0, \gamma_{500K}) = (-0.1, 0.0)$	44.49	75.42	33.44	68.78	81.00	17.13	68.50	19.10	70.25	93.25
	$(\gamma_0, \gamma_{500K}) = (0.0, 0.0)$	10.05	24.88	7.31	23.76	457.50	5.02	153.50	11.20	58.50	87.50

Table 2: Ablation on the adaptive choice of γ in Gradient-based Curriculum Learning on Howto100M dataset. We linearly decay γ during training, γ_0, γ_{500K} denote γ at the beginning and at the end of the training, respectively. *best* results are highlighted in **blue**. CL: Gradient-based Curriculum Learning. (best view in color)

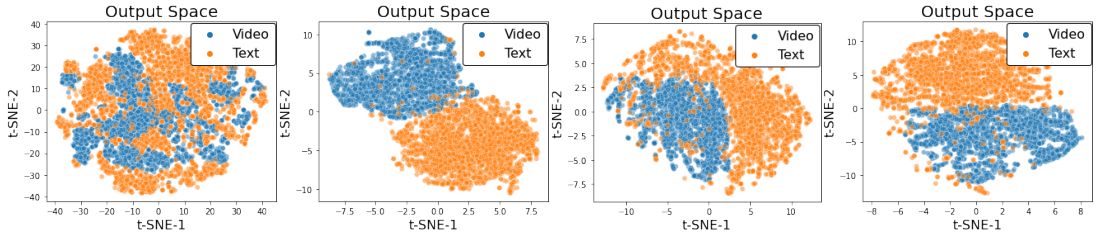
4.5 Scaling Pre-training to YouTube8M

As shown in Table 1, adding YouTube8M dataset brings the video classification and video-text retrieval performance to a new level (e.g. 88.28% Top1 on UCF101, 56.0 rank on MSRVTT)), yet it set back the performance in audio classification task, we conjecture this is largely due to the noisy misaligned samples introduced by Youtube8M dataset.

However, by leveraging our proposed techniques, we further yields a new state-of-the-art performance in the modality-agnostic setting, without any modification in architecture, striking 89.70% Top1 on UCF101, 92.15% Top5 on HMDB51, 80.01% Top1 on Kinetics400 and 85.00% Top1 on ESC50 dataset, demonstrating the effectiveness of our method when scaling to noisy Youtub8M dataset.

4.6 Feature Visualization

To better illustrate *why gradient harmonization techniques works*, in Figure 4, we follow the visualization used in VATT[11], which take YouCook2 Video-Text Retrieval dataset, showing the output space visualization of video and text, respectively. We can see the initial video and text feature representation of VATT baseline are mixed together (which aligned with the findings in [11]), however, after using gradient realignment, curriculum learning or applying both, the video and text representations become disentangled, this indicates our gradient harmonization techniques adds to cross-modality diversity, which makes video/text more discriminative from each other, making the model more discriminative and better in generalization.



(a) VATT Baseline (b) w/ Gradient Realignment (c) w/ Curriculum Learning (d) w/ Both Techniques

Figure 4: t-SNE visualization of the VATT output space on YouCook2 dataset.

5 Conclusion

In this paper, we take a deep dive into the common CMA assumption used in multimodal pre-training. Using the gradient directions between pairwise losses as the surrogate indicator, we observe ubiquitous gradient conflicts even in relatively well-aligned narrative datasets. We then propose two plug-and-play techniques to harmonize the gradients during training. They are demonstrated to substantially enhance VATT pre-training across a number of downstream tasks, and further scale it up to pre-training with even more complicated and poorly aligned data. Our findings underline the (often overlooked) importance to carefully revisit the basic assumption and training dynamics of multimodal learning, besides advancing the model architectures. However, our work did not fully explore other regularization techniques in multi-tasking learning literature, such as [26, 27, 28]. The potential negative societal impacts include the malicious use of multimodal models, such as unintended use of its downstream visual/audio recognition capability.

References

[1] Sami Abu-El-Haija, Nisarg Kothari, Joonseok Lee, Paul Natsev, George Toderici, Balakrishnan Varadarajan, and Sudheendra Vijayanarasimhan. Youtube-8m: A large-scale video classification benchmark. *arXiv preprint arXiv:1609.08675*, 2016.

[2] Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*, 2019.

[3] Ting Chen, Simon Kornblith, Mohammad Norouzi, and Geoffrey Hinton. A simple framework for contrastive learning of visual representations. In *International conference on machine learning*, pages 1597–1607. PMLR, 2020.

[4] Chen Sun, Austin Myers, Carl Vondrick, Kevin Murphy, and Cordelia Schmid. Videobert: A joint model for video and language representation learning. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 7464–7473, 2019.

[5] Jean-Baptiste Alayrac, Adria Recasens, Rosalia Schneider, Relja Arandjelovic, Jason Ramapuram, Jeffrey De Fauw, Lucas Smaira, Sander Dieleman, and Andrew Zisserman. Self-supervised multimodal versatile networks. *NeurIPS*, 2(6):7, 2020.

[6] Relja Arandjelovic and Andrew Zisserman. Look, listen and learn. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 609–617, 2017.

[7] Relja Arandjelovic and Andrew Zisserman. Objects that sound. In *Proceedings of the European conference on computer vision (ECCV)*, pages 435–451, 2018.

[8] Bruno Korbar, Du Tran, and Lorenzo Torresani. Cooperative learning of audio and video models from self-supervised synchronization. *arXiv preprint arXiv:1807.00230*, 2018.

[9] Mohammadreza Zolfaghari, Yi Zhu, Peter Gehler, and Thomas Brox. Crossclr: Cross-modal contrastive learning for multi-modal video representations. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 1450–1459, 2021.

[10] Pedro Morgado, Nuno Vasconcelos, and Ishan Misra. Audio-visual instance discrimination with cross-modal agreement. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 12475–12486, 2021.

[11] Hassan Akbari, Linagzhe Yuan, Rui Qian, Wei-Hong Chuang, Shih-Fu Chang, Yin Cui, and Boqing Gong. Vatt: Transformers for multimodal self-supervised learning from raw video, audio and text. *arXiv preprint arXiv:2104.11178*, 2021.

[12] Antoine Miech, Dimitri Zhukov, Jean-Baptiste Alayrac, Makarand Tapaswi, Ivan Laptev, and Josef Sivic. Howto100m: Learning a text-video embedding by watching hundred million narrated video clips. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 2630–2640, 2019.

[13] Antoine Miech, Jean-Baptiste Alayrac, Lucas Smaira, Ivan Laptev, Josef Sivic, and Andrew Zisserman. End-to-end learning of visual representations from uncurated instructional videos. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 9879–9889, 2020.

[14] Jue Wang, Haofan Wang, Jincan Deng, Weijia Wu, and Debing Zhang. Efficientclip: Efficient cross-modal pre-training by ensemble confident learning and language modeling. *arXiv preprint arXiv:2109.04699*, 2021.

[15] Luowei Zhou, Chenliang Xu, and Jason J Corso. Towards automatic learning of procedures from web instructional videos. In *Thirty-Second AAAI Conference on Artificial Intelligence*, 2018.

[16] Tianhe Yu, Saurabh Kumar, Abhishek Gupta, Sergey Levine, Karol Hausman, and Chelsea Finn. Gradient surgery for multi-task learning. *arXiv preprint arXiv:2001.06782*, 2020.

[17] Humam Alwassel, Dhruv Mahajan, Bruno Korbar, Lorenzo Torresani, Bernard Ghanem, and Du Tran. Self-supervised learning by cross-modal audio-video clustering. *arXiv preprint arXiv:1911.12667*, 2019.

[18] Adrià Recasens, Pauline Luc, Jean-Baptiste Alayrac, Luyu Wang, Florian Strub, Corentin Tallec, Mateusz Malinowski, Viorica Patraucean, Florent Altché, Michal Valko, et al. Broaden your views for self-supervised video learning. *arXiv preprint arXiv:2103.16559*, 2021.

[19] Huaishao Luo, Lei Ji, Botian Shi, Haoyang Huang, Nan Duan, Tianrui Li, Jason Li, Taroon Bharti, and Ming Zhou. Univl: A unified video and language pre-training model for multimodal understanding and generation. *arXiv preprint arXiv:2002.06353*, 2020.

[20] Xinlei Chen, Haoqi Fan, Ross Girshick, and Kaiming He. Improved baselines with momentum contrastive learning. *arXiv preprint arXiv:2003.04297*, 2020.

[21] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*, 2018.

[22] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. *arXiv preprint arXiv:2010.11929*, 2020.

[23] Jort F Gemmeke, Daniel PW Ellis, Dylan Freedman, Aren Jansen, Wade Lawrence, R Channing Moore, Manoj Plakal, and Marvin Ritter. Audio set: An ontology and human-labeled dataset for audio events. In *2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 776–780. IEEE, 2017.

[24] Yu Zhang and Qiang Yang. A survey on multi-task learning. *arXiv preprint arXiv:1707.08114*, 2017.

[25] Christopher Fifty, Ehsan Amid, Zhe Zhao, Tianhe Yu, Rohan Anil, and Chelsea Finn. Efficiently identifying task groupings for multi-task learning. *arXiv preprint arXiv:2109.04617*, 2021.

[26] Zhao Chen, Vijay Badrinarayanan, Chen-Yu Lee, and Andrew Rabinovich. Gradnorm: Gradient normalization for adaptive loss balancing in deep multitask networks. In *International Conference on Machine Learning*, pages 794–803. PMLR, 2018.

[27] Ozan Sener and Vladlen Koltun. Multi-task learning as multi-objective optimization. *arXiv preprint arXiv:1810.04650*, 2018.

[28] Alex Kendall, Yarin Gal, and Roberto Cipolla. Multi-task learning using uncertainty to weigh losses for scene geometry and semantics. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 7482–7491, 2018.

[29] Zirui Wang, Yulia Tsvetkov, Orhan Firat, and Yuan Cao. Gradient vaccine: Investigating and improving multi-task optimization in massively multilingual models. *arXiv preprint arXiv:2010.05874*, 2020.

[30] Weiyao Wang, Du Tran, and Matt Feiszli. What makes training multi-modal classification networks hard? In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 12695–12705, 2020.

[31] Michael Gutmann and Aapo Hyvärinen. Noise-contrastive estimation: A new estimation principle for unnormalized statistical models. In *Proceedings of the thirteenth international conference on artificial intelligence and statistics*, pages 297–304. JMLR Workshop and Conference Proceedings, 2010.

[32] Satrajit Chatterjee. Coherent gradients: An approach to understanding generalization in gradient descent-based optimization. *arXiv preprint arXiv:2002.10657*, 2020.

[33] Bo Han, Quanming Yao, Xingrui Yu, Gang Niu, Miao Xu, Weihua Hu, Ivor W Tsang, and Masashi Sugiyama. Co-teaching: robust training of deep neural networks with extremely noisy labels. In *Proceedings of the 32nd International Conference on Neural Information Processing Systems*, pages 8536–8546, 2018.

[34] Lu Jiang, Zhengyuan Zhou, Thomas Leung, Li-Jia Li, and Li Fei-Fei. Mentornet: Learning data-driven curriculum for very deep neural networks on corrupted labels. In *International Conference on Machine Learning*, pages 2304–2313. PMLR, 2018.

[35] Tianyi Zhou, Shengjie Wang, and Jeff Bilmes. Robust curriculum learning: From clean label detection to noisy label self-correction. In *International Conference on Learning Representations*, 2021.

[36] Angela H Jiang, Daniel L-K Wong, Giulio Zhou, David G Andersen, Jeffrey Dean, Gregory R Ganger, Gauri Joshi, Michael Kaminksy, Michael Kozuch, Zachary C Lipton, et al. Accelerating deep learning by focusing on the biggest losers. *arXiv preprint arXiv:1910.00762*, 2019.

[37] Linjie Li, Yen-Chun Chen, Yu Cheng, Zhe Gan, Licheng Yu, and Jingjing Liu. Hero: Hierarchical encoder for video+ language omni-representation pre-training. *arXiv preprint arXiv:2005.00200*, 2020.

[38] Andrew Jaegle, Sebastian Borgeaud, Jean-Baptiste Alayrac, Carl Doersch, Catalin Ionescu, David Ding, Skanda Koppula, Daniel Zoran, Andrew Brock, Evan Shelhamer, et al. Perceiver io: A general architecture for structured inputs & outputs. *arXiv preprint arXiv:2107.14795*, 2021.

[39] Andrew Rouditchenko, Angie Boggust, David Harwath, Brian Chen, Dhiraj Joshi, Samuel Thomas, Kartik Audhkhasi, Hilde Kuehne, Rameswar Panda, Rogerio Feris, et al. Avlnet: Learning audio-visual language representations from instructional videos. *arXiv preprint arXiv:2006.09199*, 2020.

[40] Hu Xu, Gargi Ghosh, Po-Yao Huang, Prahal Arora, Masoumeh Aminzadeh, Christoph Feichtenhofer, Florian Metze, and Luke Zettlemoyer. Vlm: Task-agnostic video-language model pre-training for video understanding. *arXiv preprint arXiv:2105.09996*, 2021.

[41] Valerii Likhosherstov, Anurag Arnab, Krzysztof Choromanski, Mario Lucic, Yi Tay, Adrian Weller, and Mostafa Dehghani. Polyvit: Co-training vision transformers on images, videos and audio. *arXiv preprint arXiv:2111.12993*, 2021.

[42] Khurram Soomro, Amir Roshan Zamir, and Mubarak Shah. Ucf101: A dataset of 101 human actions classes from videos in the wild. *arXiv preprint arXiv:1212.0402*, 2012.

[43] Hildegard Kuehne, Hueihan Jhuang, Estíbaliz Garrote, Tomaso Poggio, and Thomas Serre. Hmdb: a large video database for human motion recognition. In *2011 International conference on computer vision*, pages 2556–2563. IEEE, 2011.

[44] Will Kay, Joao Carreira, Karen Simonyan, Brian Zhang, Chloe Hillier, Sudheendra Vijayanarasimhan, Fabio Viola, Tim Green, Trevor Back, Paul Natsev, et al. The kinetics human action video dataset. *arXiv preprint arXiv:1705.06950*, 2017.

[45] Karol J Piczak. Esc: Dataset for environmental sound classification. In *Proceedings of the 23rd ACM international conference on Multimedia*, pages 1015–1018, 2015.

[46] Jun Xu, Tao Mei, Ting Yao, and Yong Rui. Msr-vtt: A large video description dataset for bridging video and language. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 5288–5296, 2016.

[47] Lucas Smaira, João Carreira, Eric Noland, Ellen Clancy, Amy Wu, and Andrew Zisserman. A short note on the kinetics-700-2020 human action dataset. *arXiv preprint arXiv:2010.10864*, 2020.

Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] See Section 5, e.g. our work did not fully explore other regularization techniques in multi-tasking learning literature, such as [26, 27, 28]
   (c) Did you discuss any potential negative societal impacts of your work? [Yes] See Section 5, e.g. the malicious use of multimodal models.
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A]
   (b) Did you include complete proofs of all theoretical results? [N/A]
3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [No] The code is proprietary, However, we include detailed discussions on experiment settings and data in Section 4.1 to replicate the experiment results.
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] See Section 4.2
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